

Survival in a quasi-death process

Erik A. van Doorn

Department of Applied Mathematics

University of Twente

P.O. Box 217, 7500 AE Enschede, The Netherlands

E-mail: e.a.vandoorn@utwente.nl

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Abstract. We consider a Markov chain in continuous time with an absorbing coffin state and a finite set S of transient states. When S is irreducible the limiting distribution of the chain as $t \rightarrow \infty$, conditional on survival up to time t , is known to equal the (unique) quasi-stationary distribution of the chain. We address the problem of generalizing this result to a setting in which S may be reducible, and obtain a complete solution if the eigenvalue with maximal real part of the generator of the (sub)Markov chain on S has multiplicity one. The result is applied to pure death processes and, more generally, to quasi-death processes.

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1 Introduction

In the interesting papers [2] and [3] Aalen and Gjessing provide a new explanation for the shape of hazard rate functions in survival analysis. They propose to model survival times as sojourn times of stochastic processes in a set S of transient states until they escape from S to an absorbing coffin state. This “process point of view” entails that (in the words of Aalen and Gjessing) “the shape of the hazard rate is created in a balance between two forces: the attraction of the absorbing state and the general diffusion within the transient space”. As a result the shape of the hazard rate is determined by the interaction of the initial distribution and the distribution over S known as the *quasi-stationary distribution* of the process. Similar ideas have been put forward independently by Steinsaltz and Evans [15].

Aalen and Gjessing discuss several examples of relevant stochastic processes, including finite-state Markov chains with an absorbing state, the setting of the present paper. A survival-time distribution in this setting is known as a *phase-type distribution* (see, for example, Aalen [1]). In their analysis and examples Aalen and Gjessing restrict themselves to chains for which the set S of transient states constitutes a single class, arguing that “irreducibility is important when considering quasistationary distributions”. As we shall see, however, there are no compelling technical reasons for imposing this restriction. Moreover, in [3, Section 8] Aalen and Gjessing allude to a bottle-neck phenomenon that may occur when S is reducible, making it even desirable to investigate what happens in this case. We note that Proposition 1 in [15], while formulated quite generally, seems to be entirely correct only if one assumes S to be irreducible.

From a modelling point of view there is another argument for extending the analysis to reducible sets S . Namely, if the status of an individual before evanescence is represented by the state of a transient Markov chain, it seems reasonable to allow for the possibility that some transitions are irreversible, reflecting the fact that some real-life processes such as *ageing* are irreversible.

The main aim of the present paper is to provide the tools for hazard rate analysis, by characterizing survival-time distributions and identifying limiting

conditional distributions and quasi-stationary distributions, in the setting of finite Markov chains with an absorbing state and a transient space S that may be reducible. In Section 2 we present some general results, which are applied in Section 3 to pure death processes. The latter results are then generalized in Section 4 to *quasi-death processes*, which may be viewed as death processes in which the sojourn time in each state has a phase-type distribution.

2 Absorbing Markov chains

Consider a continuous-time Markov chain $\mathcal{X} := \{X(t), t \geq 0\}$ on a state space $\{0\} \cup S$ consisting of an absorbing state 0 and a finite set of transient states $S := \{1, 2, \dots, n\}$. The generator of \mathcal{X} then takes the form

$$\begin{pmatrix} 0 & \mathbf{0} \\ \mathbf{q}^T & Q \end{pmatrix}, \quad (1)$$

where

$$\mathbf{q} = -\mathbf{1}Q^T > \mathbf{0}. \quad (2)$$

Here $\mathbf{0}$ and $\mathbf{1}$ are row vectors of zeros and ones, respectively, superscript T denotes transpose, and strict inequality for vectors indicates strict inequality in at least one component. Since all states in S are transient, state 0 is accessible from any state in S . Hence, whichever the initial state, the process will eventually escape from S into the absorbing state 0 with probability one.

We write $\mathbb{P}_i(\cdot)$ for the probability measure of the process when $X(0) = i$, and let $\mathbb{P}_{\mathbf{w}}(\cdot) := \sum_i w_i \mathbb{P}_i(\cdot)$ for any vector $\mathbf{w} = (w_1, w_2, \dots, w_n)$ representing a distribution over S . Also, $P_{ij}(\cdot) := \mathbb{P}_i(X(\cdot) = j)$. It is easy to verify (see, for example, Kijima [8, Section 4.6]) that the matrix $P(t) := (P_{ij}(t), i, j \in S)$ satisfies

$$P(t) = e^{Qt} := \sum_{k=0}^{\infty} \frac{Q^k}{k!} t^k, \quad t \geq 0.$$

By $T := \sup\{t \geq 0 : X(t) \in S\}$ we denote the *survival time* (or *absorption time*) of \mathcal{X} , the random variable representing the time at which escape from

S occurs. In what follows we are interested in the limiting distribution of the residual survival time conditional on survival up to time t , that is,

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(T \leq t + s \mid T > t), \quad s \geq 0, \quad (3)$$

and in the limiting distribution of $X(t)$ conditional on survival up to time t , that is,

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(X(t) = j \mid T > t), \quad j \in S, \quad (4)$$

where \mathbf{w} is any initial distribution over S .

Let us first suppose that S is irreducible, that is, constitutes a single communicating class. In this case Q has a unique eigenvalue with maximal real part, which we denote by $-\alpha$. It is well known (see, for example, Seneta [14, Theorem 2.6]) that α is real and positive, and that the associated left and right eigenvectors $\mathbf{u} = (u_1, u_2, \dots, u_n)$ and $\mathbf{v} = (v_1, v_2, \dots, v_n)$ can be chosen strictly positive componentwise. It will also be convenient to normalize \mathbf{u} and \mathbf{v} such that

$$\mathbf{u}\mathbf{1}^T = 1 \quad \text{and} \quad \mathbf{u}\mathbf{v}^T = 1. \quad (5)$$

It then follows (see Mandl [12]) that the transition probabilities $P_{ij}(t)$ satisfy

$$\lim_{t \rightarrow \infty} e^{\alpha t} P_{ij}(t) = v_i u_j, \quad i, j \in S, \quad (6)$$

which explains why α is often referred to as the *decay parameter* of \mathcal{X} . We shall show later (Theorem 4) that (6) actually holds true in a more general setting.

Since $\mathbf{u}Q = -\alpha\mathbf{u}$, we have $\mathbf{u}Q^k = (-\alpha)^k\mathbf{u}$ for all k , and hence

$$\mathbf{u}P(t) = \sum_{k=0}^{\infty} \frac{\mathbf{u}Q^k}{k!} t^k = e^{-\alpha t} \mathbf{u}, \quad t \geq 0,$$

that is

$$\mathbb{P}_{\mathbf{u}}(X(t) = j) = e^{-\alpha t} u_j, \quad j \in S, \quad t \geq 0. \quad (7)$$

Since $\mathbb{P}_{\mathbf{u}}(T > t) = \mathbb{P}_{\mathbf{u}}(X(t) \in S) = e^{-\alpha t}$, it follows that for all $t \geq 0$

$$\mathbb{P}_{\mathbf{u}}(T > t + s \mid T > t) = e^{-\alpha s}, \quad s \geq 0. \quad (8)$$

Moreover, \mathbf{u} is a *quasi-stationary distribution* of \mathcal{X} in the sense that for all $t \geq 0$

$$\mathbb{P}_{\mathbf{u}}(X(t) = j \mid T > t) = u_j, \quad j \in S, \quad (9)$$

that is, the distribution of $X(t)$ conditional on absorption not yet having taken place at time t is constant over t when \mathbf{u} is the initial distribution. Darroch and Seneta [5] have shown that similar results hold true in the limit as $t \rightarrow \infty$ when the initial distribution differs from \mathbf{u} . Namely, for any initial distribution \mathbf{w} one has

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(T > t + s \mid T > t) = e^{-\alpha s}, \quad s \geq 0, \quad (10)$$

and

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(X(t) = j \mid T > t) = u_j, \quad j \in S. \quad (11)$$

So when all states in S communicate the limits (3) and (4) are determined by the largest eigenvalue of Q and the corresponding left eigenvector.

This result can be generalized, at least in principle, to a setting in which S consists of more than one class. Indeed, suppose that S consists of communicating classes S_1, S_2, \dots, S_c , and let Q_k be the submatrix of Q corresponding to the states in S_k . Obviously, the set of eigenvalues of Q is precisely the union of the sets of eigenvalues of the individual Q_k 's. So, if we denote the (unique) eigenvalue with maximal real part of Q_k by $-\alpha_k$ (so that α_k is real and positive), and let $\alpha := \min_k \alpha_k$, then $-\alpha$ is the eigenvalue of Q with maximal real part. Evidently, $-\alpha$ may be degenerate, but we will restrict ourselves to settings in which $-\alpha$ has algebraic (and hence geometric) multiplicity one. Under this condition then there exist, up to constant factors, unique left and right eigenvectors \mathbf{u} and \mathbf{v} corresponding to $-\alpha$. It follows from Theorem I* of Debreu and Herstein [6] (by an argument similar to the proof of [14, Theorem 2.6]) that we may choose $\mathbf{u} > \mathbf{0}$, $\mathbf{v} > \mathbf{0}$ and $\mathbf{u}\mathbf{1}^T = 1$, but \mathbf{u} and \mathbf{v} are not necessarily positive componentwise.

In the present setting (7), and hence (8) and (9), retain their validity. Letting

$$a(\alpha) := \arg \min_k \alpha_k, \quad (12)$$

we note that $S_{a(\alpha)}$ must be accessible from \mathbf{u} (that is, accessible from a state i such that $u_i > 0$). Indeed, α having multiplicity one, the opposite would imply that (8) cannot be true. It is well known that $\mathbb{P}_{\mathbf{u}}(X(t) = j) > 0$ for all $t > 0$ if and only if j is accessible from \mathbf{u} , so it follows from (7) that we must actually have $u_j > 0$ for all states j that are accessible from \mathbf{u} , and in particular for all states j that are accessible from $S_{a(\alpha)}$. On the other hand, \mathbf{u} being the unique solution of the system $\mathbf{u}Q = -\alpha\mathbf{u}$ and $\mathbf{u}\mathbf{1}^T = 1$, we must have $u_j = 0$ if j is *not* accessible from $S_{a(\alpha)}$. For it is easily seen that we can determine \mathbf{u} by first solving the eigenvector problem in the restricted setting of states that are accessible from $S_{a(\alpha)}$, and subsequently putting $u_j = 0$ whenever j is not accessible from $S_{a(\alpha)}$. So $u_j > 0$ if and only if state j is accessible from $S_{a(\alpha)}$. The counterpart of (7) for the right eigenvector \mathbf{v} is the relation

$$\sum_{j \in S} P_{ij}(t)v_j = e^{-\alpha t}v_i, \quad i \in S, \quad (13)$$

which may be used in a similar way to show that $v_i > 0$ if and only if $S_{a(\alpha)}$ is accessible from i . It follows in particular that both $u_j > 0$ and $v_j > 0$ if (and only if) $j \in S_{a(\alpha)}$, so that \mathbf{v} may be normalized such that $\mathbf{u}\mathbf{v}^T = 1$. We summarize our findings in the next theorem.

Theorem 1 If $-\alpha$, the eigenvalue of Q with maximal real part, has multiplicity one, then there are unique nonnegative vectors \mathbf{u} and \mathbf{v} satisfying $\mathbf{u}Q = -\alpha\mathbf{u}$, $Q\mathbf{v}^T = -\alpha\mathbf{v}^T$, $\mathbf{u}\mathbf{1}^T = 1$, and $\mathbf{u}\mathbf{v}^T = 1$. The i th component of \mathbf{u} is positive if and only if state i is accessible from $S_{a(\alpha)}$, whereas the i th component of \mathbf{v} is positive if and only if $S_{a(\alpha)}$ is accessible from state i .

The vector \mathbf{u} does not necessarily constitute the only quasi-stationary distribution of the process \mathcal{X} , that is, the only initial distribution satisfying (9) for all $t \geq 0$. However, we can achieve uniqueness if we restrict ourselves to initial distributions from which $S_{a(\alpha)}$ is accessible. To prove this statement we need the following invariance result.

Lemma 2 If the initial distribution \mathbf{w} is such that $S_{a(\alpha)}$ is accessible, and satisfies $\mathbf{w}Q = x\mathbf{w}$ for some $x < 0$, then $x = -\alpha$ and $\mathbf{w} = \mathbf{u}$.

Proof When the initial distribution $\mathbf{w} = (w_1, w_2, \dots, w_n)$ is a left eigenvector corresponding to the eigenvalue x , then, by an argument similar to the one leading to (7), we have

$$\mathbb{P}\mathbf{w}(X(t) = j) = e^{xt}w_j, \quad j \in S, \quad t \geq 0.$$

It follows that $w_j > 0$ for all states j that are accessible from \mathbf{w} . So, if $S_{a(\alpha)}$ is accessible from \mathbf{w} , then $w_j > 0$ for all $j \in S_{a(\alpha)}$. Hence, by Theorem 1, $\mathbf{w}\mathbf{v}^T > 0$. Since $\mathbf{w}Q = x\mathbf{w}$ implies $x\mathbf{w}\mathbf{v}^T = \mathbf{w}Q\mathbf{v}^T = -\alpha\mathbf{w}\mathbf{v}^T$, we must have $x = -\alpha$, and hence $\mathbf{w} = \mathbf{u}$. \square

We can now copy the arguments in [5] (in which a similar invariance result is implicitly used) and conclude the following.

Theorem 3 If $-\alpha$, the eigenvalue of Q with maximal real part, has multiplicity one, then \mathcal{X} has a unique quasi-stationary distribution \mathbf{u} from which $S_{a(\alpha)}$ is accessible. The vector \mathbf{u} is the (unique, nonnegative) solution of the system $\mathbf{u}Q = -\alpha\mathbf{u}$ and $\mathbf{u}\mathbf{1}^T = 1$.

To determine the limits (10) and (11) in the general setting at hand we need the announced generalization of (6). Its proof is similar to the proof of Theorem 1 in [12], but since this reference is in Russian we sketch the argument.

Theorem 4 If $-\alpha$, the eigenvalue of Q with maximal real part, has multiplicity one then

$$\lim_{t \rightarrow \infty} e^{\alpha t} P(t) = \mathbf{v}^T \mathbf{u}, \quad (14)$$

where \mathbf{u} and \mathbf{v} are the eigenvectors defined in Theorem 1.

Proof With $J = (J_{ij})$ denoting the Jordan canonical form of Q , there exists a nonsingular matrix $S = (S_{ij})$ such that $Q = SJS^{-1}$, and hence

$$P(t) = e^{tQ} = Se^{tJ}S^{-1}, \quad t \geq 0.$$

Since $J_{11} = -\alpha$, while $J_{1j} = J_{j1} = 0$ if $j \neq 1$, it follows that

$$P_{ij}(t) = e^{-\alpha t} S_{i1}(S^{-1})_{1j} + o(e^{-\alpha t}) \quad \text{as } t \rightarrow \infty, \quad i, j \in S,$$

and hence

$$\lim_{t \rightarrow \infty} e^{\alpha t} P(t) = \mathbf{s}^T \mathbf{t},$$

where \mathbf{s}^T denotes the first column of S and \mathbf{t} the first row of S^{-1} . Since $QS = SJ$ we must have $Q\mathbf{s}^T = -\alpha\mathbf{s}^T$, so we can normalize \mathbf{s} such that $\mathbf{s} = \mathbf{v}$. Moreover, by the Markov property,

$$e^{-\alpha s} \mathbf{v}^T \mathbf{t} = e^{-\alpha s} \lim_{t \rightarrow \infty} e^{\alpha(t+s)} P(t+s) = \mathbf{v}^T \mathbf{t} P(s).$$

Pre-multiplying this relation by \mathbf{u} we obtain $e^{-\alpha s} \mathbf{t} = \mathbf{t} P(s)$. Subsequently taking derivatives with respect to s , and letting $s \downarrow 0$ yields $-\alpha \mathbf{t} = \mathbf{t} Q$. Finally, since $\mathbf{t} \mathbf{v}^T = \mathbf{t} \mathbf{s}^T = 1$, we must have $\mathbf{t} = \mathbf{u}$. \square

We can now copy the argument in [12] or [5] to conclude the following.

Theorem 5 If $-\alpha$, the eigenvalue of Q with maximal real part, has multiplicity one, and the initial distribution \mathbf{w} is such that $S_{a(\alpha)}$ is accessible, then the limits (3) and (4) exist and are given by (10) and (11), respectively, where \mathbf{u} is the unique quasi-stationary distribution from which $S_{a(\alpha)}$ is accessible.

Remark The results in [12] and [5] constitute the continuous-time counterparts of results obtained in [11] and [4], respectively, in a discrete-time setting. The latter results have been generalized (in a more abstract, but still discrete, setting) by Lindqvist [10]. An alternative approach towards proving Theorem 5 would be to take Lindqvist results (in particular [10, Theorem 5.8]) as a starting point and prove their analogues in a continuous setting. In this way an even more general statement would result (allowing a degenerate eigenvalue $-\alpha$ under certain conditions), but at the cost of a more elaborate notation and formulation.

The fact that the limiting distribution of the residual survival time exists and is exponentially distributed has been observed by Kalpakam [7] and Li and Cao [9] in a somewhat more general setting, namely when the Laplace transform of the survival-time distribution is a rational function (cf. [13]).

In what follows we are interested in particular in properties of the left eigenvector \mathbf{u} that are determined by structural properties of Q . To set the stage we first look more closely into the simple multi-class setting of a pure death process in the next section, and then generalize our results to quasi-death processes in Section 4.

3 Pure death processes

Let us assume that the Markov chain $\mathcal{X} = \{X(t), t \geq 0\}$ of the previous section is a pure death process with death rate μ_i in state $i \in S$, so that the matrix Q of (1) is given by

$$Q = \begin{pmatrix} -\mu_1 & 0 & 0 & . & . & . & 0 & 0 & 0 \\ \mu_2 & -\mu_2 & 0 & . & . & . & 0 & 0 & 0 \\ . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . \\ 0 & 0 & 0 & . & . & . & 0 & \mu_n & -\mu_n \end{pmatrix}. \quad (15)$$

Evidently, the classes of S now consist of single states, so, maintaining the notation of the previous section, we let $S_k = \{k\}$, and find that $\alpha_k = \mu_k$ and

$$\alpha = \mu := \min_{i \in S} \mu_i. \quad (16)$$

As before, we assume that μ is a nondegenerate eigenvalue of Q , whence

$$a := \arg \min_{i \in S} \mu_i \quad (17)$$

is uniquely defined. It is clear that an initial distribution \mathbf{w} satisfies the requirements of Theorem 5 if and only if \mathbf{w} has support in the set of states $\{a, a+1, \dots, n\}$. Theorem 5 therefore implies the following, where an empty product denotes unity.

Theorem 6 Let \mathcal{X} is a pure death process with death rate μ_i in state $i \in S$, and a unique state a such that $\mu_a = \min_{i \in S} \mu_i$. If the initial distribution \mathbf{w} is supported by at least one state $i \geq a$, then

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(T > t + s | T > t) = e^{-\mu s}, \quad s \geq 0. \quad (18)$$

and

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(X(t) = j \mid T > t) = u_j, \quad j \in S, \quad (19)$$

where $\mathbf{u} = (u_1, u_2, \dots, u_n)$ is the (unique) quasi-stationary distribution of \mathcal{X} from which $S_{a(\alpha)}$ is accessible, and given by

$$u_j = \begin{cases} \frac{\mu}{\mu_j} \prod_{i=1}^{j-1} \left(1 - \frac{\mu}{\mu_i}\right), & j < a \\ \prod_{i=1}^{a-1} \left(1 - \frac{\mu}{\mu_i}\right), & j = a \\ 0, & j > a. \end{cases} \quad (20)$$

Proof By Theorems 3 and 5 we have to show that the vector \mathbf{u} satisfies $\mathbf{u}Q = -\mu\mathbf{u}$ and $\mathbf{u}\mathbf{1}^T = 1$. It is a routine exercise to verify these properties. \square

Example The quasi-stationary distribution of the death process on $S = \{0, 1, 2\}$ is given by

$$\mathbf{u} = (u_1, u_2) = \begin{cases} \left(\frac{\mu_2}{\mu_1}, 1 - \frac{\mu_2}{\mu_1}\right) & \text{if } \mu_2 < \mu_1 \\ (1, 0) & \text{if } \mu_1 < \mu_2. \end{cases} \quad (21)$$

In view of Theorem 5 we conclude that state 1 is a *bottle-neck* state when $\mu_1 < \mu_2$, in the sense that the process is almost surely in state 1 if, after a long time, absorption has not yet occurred, whatever the initial distribution. This is an example of the phenomenon alluded to by Aalen and Gjessing in [3, Section 8]. Note that $(1, 0)$ is also a quasi-stationary distribution if $\mu_2 < \mu_1$, but one from which state 2 is not accessible. So it is a limiting conditional distribution only if $\mathbb{P}(X(0) = 2) = 0$. \square

As an aside we remark that the survival time in any birth-death process can be represented by the survival time in a pure death process with the same number of states (see, for example, Aalen [1]). Evidently, the quasi-stationary distributions of the two processes will be different in general.

4 Quasi-death processes

The absorbing continuous-time Markov chain $\mathcal{X} := \{X(t), t \geq 0\}$ of Section 2 is a *quasi-death process* if $S = \{(\ell, j) \mid \ell = 1, 2, \dots, L, j = 1, 2, \dots, J_\ell\}$ and Q takes the block-partitioned form

$$Q = \begin{pmatrix} Q_1 & 0 & 0 & . & . & 0 & 0 & 0 \\ M_2 & Q_2 & 0 & . & . & 0 & 0 & 0 \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . \\ 0 & 0 & 0 & . & . & 0 & M_L & Q_L \end{pmatrix}, \quad (22)$$

where Q_ℓ and M_ℓ are nonzero matrices of dimension $J_\ell \times J_\ell$, and $J_\ell \times J_{\ell-1}$, respectively. We write $X(t) = (L(t), J(t))$ and call $L(t)$ the *level* and $J(t)$ the *phase* of the process at time $t < T$. Throughout this section we assume that $S_\ell := \{(\ell, j) \mid j = 1, 2, \dots, J_\ell\}$ is a communicating class for each level ℓ . Moreover, we suppose

$$\mathbf{1}M_\ell^T + \mathbf{1}Q_\ell^T = \mathbf{0}, \quad \ell = 2, 3, \dots, L, \quad (23)$$

and, to be consistent with (2),

$$\mathbf{q}_1 := -\mathbf{1}Q_1^T > \mathbf{0}. \quad (24)$$

Hence, with probability one and for any initial state (ℓ, i) , the function $L(t)$, $0 \leq t < T$, will be a step function with downward jumps of size one, and the process will eventually escape from S , via a state at level 1, to the absorbing state 0. Extending the notation introduced in Section 2 we write

$$\mathbb{P}\mathbf{w}_\ell(\cdot) := \sum_{i=1}^{J_\ell} w_{\ell i} \mathbb{P}_{(\ell, i)}(\cdot)$$

for any distribution $\mathbf{w}_\ell = (w_{\ell 1}, w_{\ell 2}, \dots, w_{\ell J_\ell})$ over S_ℓ .

Evidently, if $J_\ell = 1$ for all levels ℓ then we are in the setting of the simple death process of the previous section with death rate $\mu_1 := \mathbf{q}_1$ in state 1 and $\mu_\ell := M_\ell$ in state $\ell > 1$. On the other hand, if the initial distribution concentrates all mass on the first level, we are basically dealing with a Markov chain taking values in the set $\{0\} \cup S_1$, with 0 an absorbing state and S_1 a single

communicating class, a setting discussed in the beginning of Section 2. In the general setting at hand we must apply Theorems 3 and 5, but, as we shall see, we can reduce the amount of computation by exploiting the structure of Q .

We denote the (unique) eigenvalue of Q_ℓ with maximal real part by $-\alpha_\ell$, and the associated left and right eigenvectors by $\mathbf{x}_\ell = (x_{\ell 1}, x_{\ell 2}, \dots, x_{\ell J_\ell})$ and $\mathbf{y}_\ell = (y_{\ell 1}, y_{\ell 2}, \dots, y_{\ell J_\ell})$, respectively. As noted before, α_ℓ is real and positive, and \mathbf{x}_ℓ and \mathbf{y}_ℓ can be chosen strictly positive componentwise and such that

$$\mathbf{x}_\ell \mathbf{1}^T = 1 \quad \text{and} \quad \mathbf{x}_\ell \mathbf{y}_\ell^T = 1. \quad (25)$$

In analogy to (6) we have

$$\lim_{t \rightarrow \infty} e^{\alpha_\ell t} P_{(\ell, i), (\ell, j)}(t) = y_{\ell i} x_{\ell j}, \quad i, j = 1, 2, \dots, J_\ell, \quad (26)$$

for each level ℓ , so we will refer to α_ℓ as the *decay parameter of \mathcal{X} in S_ℓ* . Moreover, the vector \mathbf{x}_ℓ can be interpreted as the *quasi-stationary distribution of \mathcal{X} in S_ℓ* , in the sense that

$$\mathbb{P}_{\mathbf{u}_\ell}(X(t) = (\ell, j) \mid T_\ell > t) = x_{\ell j}, \quad t \geq 0, \quad j = 1, 2, \dots, J_\ell, \quad (27)$$

where T_ℓ denotes the sojourn time of \mathcal{X} in S_ℓ , while

$$\mathbb{P}_{\mathbf{u}_\ell}(T_\ell > t) = e^{-\alpha_\ell t}, \quad t \geq 0. \quad (28)$$

If the initial distribution concentrates all mass in S_ℓ (and is represented by the vector $\mathbf{w}_\ell = (w_{\ell 1}, w_{\ell 2}, \dots, w_{\ell J_\ell})$, say) but is otherwise arbitrary, then, by the results of Darroch and Seneta [5] mentioned in Section 2,

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}_\ell}(X(t) = (\ell, j) \mid T_\ell > t) = x_{\ell j}, \quad j = 1, 2, \dots, J_\ell, \quad (29)$$

and

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}_\ell}(T_\ell > t + s \mid T_\ell > t) = e^{-\alpha_\ell s}, \quad s \geq 0. \quad (30)$$

Now turning to a general initial distribution $\mathbf{w} = (\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_L)$, where $\mathbf{w}_\ell = (w_{\ell 1}, w_{\ell 2}, \dots, w_{\ell J_\ell})$ for $\ell = 1, 2, \dots, L$, Theorem 5 tells us that the limiting distribution of the residual survival time in $S = \cup_\ell S_\ell$ is exponentially distributed with parameter $\alpha = \min_k \alpha_k$. As regards the limiting distribution of $X(t)$ conditional on survival in S up to time t , we can finally state the following generalization of Theorem 6.

Theorem 7 Let \mathcal{X} be a quasi-death process for which Q takes the form (22), and which has a unique level a such that $\alpha_a = \min_\ell \alpha_\ell$. If the initial distribution \mathbf{w} is supported by at least one state in the set $\cup_{\ell \geq a} S_\ell$, then

$$\lim_{t \rightarrow \infty} \mathbb{P}_{\mathbf{w}}(X(t) = (\ell, j) \mid T > t) = u_{\ell j}, \quad j = 1, 2, \dots, J_\ell, \quad \ell = 1, 2, \dots, L, \quad (31)$$

where $\mathbf{u}_\ell := (u_{\ell 1}, u_{\ell 2}, \dots, u_{\ell J_\ell})$ satisfies $\mathbf{u}_\ell = \mathbf{0}$ if $\ell > a$, and $\mathbf{u}_a = c\mathbf{x}_a$, with \mathbf{x}_a the (unique and strictly positive) solution of

$$\mathbf{x}_a Q_a = -\alpha \mathbf{x}_a, \quad \mathbf{x}_a \mathbf{1}^T = 1; \quad (32)$$

for $\ell < a$, \mathbf{u}_ℓ is recursively defined by

$$\mathbf{u}_\ell = -\mathbf{u}_{\ell+1} M_{\ell+1} (Q_\ell + \alpha I)^{-1}. \quad (33)$$

Here I is an identity matrix of appropriate dimensions and $c > 0$ is such that $\mathbf{u} \mathbf{1}^T = 1$, where $\mathbf{u} := (\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_L)$.

Proof Since, for all $\ell \neq a$, the matrix $Q_\ell + \alpha I$ has largest eigenvalue $-(\alpha_\ell - \alpha) < 0$, it follows from [14, Theorem 2.6(g)] that $-(Q_\ell + \alpha I)^{-1}$ exists and has strictly positive components. So, by induction, \mathbf{u}_ℓ is positive componentwise for $\ell \leq a$. It follows easily that the vector \mathbf{u} satisfies the requirements of Theorem 3. \square

References

- [1] Aalen, O.O. (1995) Phase type distributions in survival analysis. *Scand. J. Statist.* **22**, 447-463.
- [2] Aalen, O.O. and Gjessing, H.K. (2001) Understanding the shape of the hazard rate: a process point of view. *Statist. Sci.* **16**, 1-22.
- [3] Aalen, O.O. and Gjessing, H.K. (2003) A look behind survival data: underlying processes and quasi-stationarity. In: Lindqvist, B.H. and Doksum, K.A. (Eds.), *Mathematical and Statistical Methods in Reliability*. World Scientific Publishing, Singapore, pp. 221-234.
- [4] Darroch, J.N. and Seneta, E. (1964) On quasi-stationary distributions in absorbing discrete-time finite Markov chains. *J. Appl. Probab.* **2**, 88-100.

- [5] Darroch, J.N. and Seneta, E. (1967) On quasi-stationary distributions in absorbing continuous-time finite Markov chains. *J. Appl. Probab.* **4**, 192-196.
- [6] Debreu, G. and Herstein, I.N. (1953) Nonnegative square matrices. *Econometrica* **21**, 597-607.
- [7] Kapalkam, S. (1993) On the quasi-stationary distribution of the residual lifetime. *IEEE Trans. Reliab.* **42**, 623-624.
- [8] Kijima, M. *Markov Processes for Stochastic Modeling*. Chapman & Hall, London, 1997.
- [9] Li, W. and Cao, J. (1993) The limiting distributions of the residual lifetimes of a Markov repairable system. *Reliab. Eng. System Safety* **41**, 103-105.
- [10] Lindqvist, B.H. (1989) Asymptotic properties of powers of nonnegative matrices, with applications. *Linear Algebra Appl.* **114/115**, 555-588.
- [11] Mandl, P. (1959) On the asymptotic behaviour of probabilities within groups of states of a homogeneous Markov chain. *Časopis Pěst. Mat.* **84**, 140-149 (in Russian).
- [12] Mandl, P. (1960) On the asymptotic behaviour of probabilities within groups of states of a homogeneous Markov process. *Časopis Pěst. Mat.* **85**, 448-455 (in Russian).
- [13] O'Cinneide, C.A. (1990) Characterization of phase type distributions. *Stoch. Models* **6**, 1-57.
- [14] Seneta, E. *Non-negative Matrices and Markov Chains*, rev. ed., Springer, New York, 1981.
- [15] Steinsaltz, D. and Evans, S.N. (2004) Markov mortality models: implications of quasistationarity and varying initial distributions. *Theoret. Population Biol.* **65**, 319-337.